Energy Detection in Medical Telemetry Systems using Logarithmic Adaptive Algorithm

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Abstract *— In cognitive radio, spectrum sensing is one of the key issues. It prevents the harmful interference with the licensed users and it has to improve the spectrum's utilization, for that it has to identify the available spectrum. Spectrum sensing in the cognitive radio systems enables to detect the unused portions of radio spectrum. The patient isn't treated in time in real time scenario, if he is far away from hospital. Medical telemetry network plays a major role for this type of cases. Telemetry is mainly useful for the patients who are at a risk of abnormal heart activity. In wireless sensor networks, medical body area networks (MBAN) is a human-centric application which has more significance. For spectrum sensing, energy detection is mostly used technique. Energy detection doesn't need of any previous data for aspect of primary user (PU) signal. In telemetry network problems due to the energy detection can be solved by proposed Error Normalized Least Mean Logarithmic Square (ENLMLS) methods. Results shows that the performance of dynamic selection of threshold which measures noise level of the signal in received signal gives better simulation in terms of increasing probability detection and decreasing false alarm.*

Keywords *— Cognitive radio, Energy detection, Health Care Monitoring, Medical Telemetry, probability detection, false alarm, Spectrum sensing, Threshold.*

I. INTRODUCTION

Energy detection is a simple and optimal method that could be applied to any spectrum without any prior information about signal in order to determine whether a certain signal of bandwidth is free or not at a particular time. And also, Spectrum sensing has been a crucial problem since decades. Spectrum sensing can be done by Energy detection in primary user's (PU) channel and interferences can also be avoided. Observation of primary user channels plays an important role in adapting secondary user's (SU) transmission strategies. Though there are numerous solutions for classifying primary user (PU) patterns, dynamically these approaches couldn't retrieve greater results for traffic patterns [1]. Energy Detection depends on Signal-to-Noise Ratio (SNR). We cannot select static threshold while sensing an unused spectrum as the noise ratio varies with time. By choosing dynamic threshold we can retrieve greater results. Fast Fourier Transform (FFT) is one of the spectrum sensing techniques that increases the probability of spectrum sensing when there are a greater number of samples [2]. Certain fixed spectrum allocation leads to wastage of lots of frequency bands which is of high cost [3]. There are two scenarios in spectrum allocation. First scenario is underutilization which means a smaller number of users in a particular spectrum. Second scenario is overutilization where there is a greater number of users than expected and leads to shortage of spectrum. Then cognitive radios were invented to intelligently detect free spectrums that are not being used by primary users and allocate them to secondary users. And also, if there is over utilization, it searches for free spectrum in other location and assigns the primary user to it [4]-[8]. As most of the RF spectrum is being wasted by the primary users, Cognitive radio technology came into existence to overcome this problem. Cognitive radio is a form of wireless communication that intelligently detects whether the spectrum is occupied by PU's or not. We can decrease the probability of false alarm by implementing better solutions. There are numerous things that give false alarm in energy detection. Laplacian noise is one of the several noises that lead to detection of false alarm [9]. Even though several techniques were introduced for spectrum sensing like eigen-value technique, Wishart distribution etc, when there is non-AWGN noise in the background it could lead to false alarm detection and to get rid of this, Laplacian distribution techniques has been introduced. Replacement of power 2 of amplitude of receiver signal technique with p-arbitrary power operation has been discussed in [10]-[14] which enhance the detection technique. Cognitive Systems that is developed, it is having various signal processing capabilities and it is based on software defined radio (SDR), it also supports Dynamic Spectrum Access [5]. Medical telemetry is something that is very helpful healthcare industry. It uses the Radio Frequency (RF) communication. Electrical signals tracks and controls your heartbeat. For primary or secondary users' existence in Wireless Medical Telemetry Service (WTMS) works under three types of frequency bands they are 608 to 614 MHz, 1395 to 1400 MHz, and 1427 to 1432 MHz. Using frequencies other than these may lead to noise, disconnection etc. Nevertheless, security is one of the major concerns in medical telemetry as it may lead to security breach and could harm patient's health [15]. It is imposing different variants to filter parameters of adaptive filters. By using these constraints, analysis of adaptive filter and their derivations are measured. In general, signal processing problems are due to noisy signals. To recover the noise problems measurements systems is generally designed. Computational complexity problems are reduced by adapting signal processing problems and then updating partial coefficients. By using this partially updated adaptive filters, performance is improved by reducing complexity. Error of adaptive filter is reduced by taking difference between the output filter and desired signal. For signal processing, various adaptive filter methods are available. Least Mean Square (LMS) is type of adaptive filter that finds the filter coefficients that relate to producing LMS of the error signal. But this filter is adapted based on error only at the current time [16]. LMS is sensitive for scaling of its input, due to this it is difficulty to stabilize the algorithm. To ensure better learning rate and smooth operation of such a system, the network must exhibit intelligence and able to cope up with rapid changes in the process of energy detection. This is achieved by using Error Normalized Least Mean Logarithmic Square (ENLMLS) adaptive filter that normalizes the learning rate with respect to time varying system. Noise signal n(P) and input signal b(P) are used for updating adaptive filter coefficients with w(P). In ENLMLS, if there is no interference the optimal learning rate would be 1. This is a cyclic process that will be updated on its own. And this shows better performance compared to above methods. However, choosing reliable biomedical sensors, wearable's etc is also a crucial thing in treating patients remotely despite the communication methods we improved. Everyone is facing a lot of problems in getting proper treatment in this current scenario (COVID-19) and we can provide better solution to this problem by implementing proper Medical Body Area Network (MBAN) and dedicated technology based on cognitive radio algorithms [17]. We can provide multiple solutions like remote treatment, prior booking of beds in hospital online etc. As stated in [18] more than 50% of the deaths are of non-transmissible diseases. Considering current COVID-19 situation along with that, we could say Wireless Medical Telemetry Service (WTMS) plays a vital role in saving numerous lives. There are several things such as wearable nodes or implantable on body under Medical Body Area Network (MBAN) that are responsible for a patient health. We could say that WBAN is an IoT application. The sensors planted on the patient's body collects necessary data for every predetermined interval of time. And they are connected to a point where data of all the sensors is gathered and pre-processed. And again, this data is sent to doctors/hospital management wirelessly through a Wi-Fi, Bluetooth etc. We need to implement better wireless to communication techniques for seamless connection, maintaining data without any loss on transmission & QoS [19]. Medical wireless body area network decreasing health care expenditures [20] – [24]. Patients physiological data obtained by using MWBAN, then there is a capability of processing, sampling and communication will be done for various signals [25]. Apart of these several communications, signal strategies in this contest are reported in [26]-[30].

The remainder of the paper is organized as follows. In Section II proposed Error Normalized LMLS algorithm using ED algorithm is illustrated and its performance is analysed. Section III provides numerical simulations to verify the validity of proposed algorithm. Finally, the conclusion of this paper is given in Section IV.

II. ENLMLS FOR SPECTRUM SENSING

Energy detection doesn't involve any basic knowledge about transmission from primary user. It will detect energy from the receiver end. Energy Detection technique will provide many advantages in terms of applications. Also, Energy detection has a disadvantage of high noise uncertainty. In cognitive radios, spectrum sensing is one of the aspects. Cognitive radio will track the available spectrum bands in the neighbourhood to identify its primary users and spectrum holes. In cognitive radio systems, spectrum sensing is used for identifying primary user is available or not. To increase efficiency of the present spectrum the cognitive radio technology is applied. The cognitive radio will estimate the level of energy for certain time period. In spectrum sensing the primary users search for the holes in the frequency bands and if the holes found primary user will transmit to that frequency. But it is difficult to search whole frequency ranges for the cognitive radio, so we use energy detection technique its block diagram is shown in figure 1. This energy detector

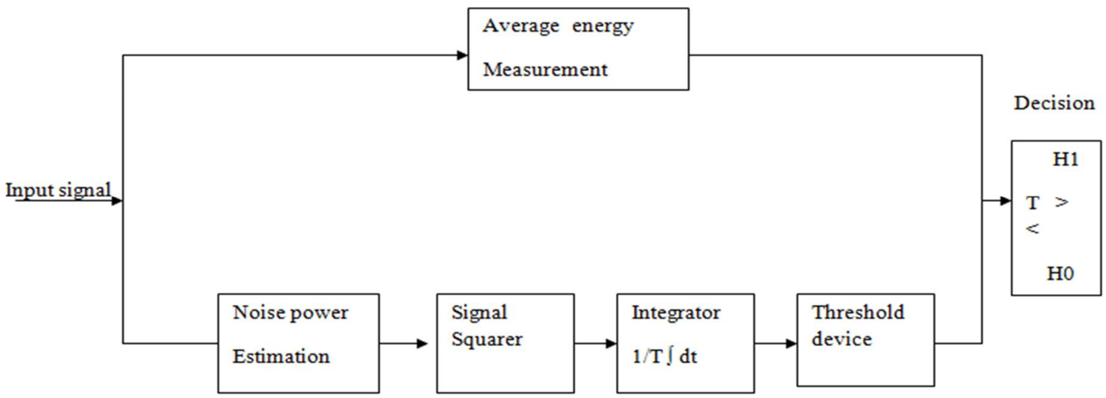

Figure 1: Block diagram for spectrum sensing using energy detection

Based on the hypothesis the spectrum is given as follows

$$H(a): \; a(P) = b(P)$$

$$H(b): \; a(P) = b(P) + n(P)$$

Where, H (a) is taken when primary user is available, H (b) is taken when primary user is not available

a (P) is by secondary user, signal is received

b (P) is by the primary user, signal is transmitted,

n (P) is noise present in signal.

By using band pass filter, input signal is transmitted. Band pass filter will limit the bandwidth of output signal. Then, the signal is given to a squarer to calculate the energy which will go through the integrated block. The output of the band pass filter and squaring is integrated over a time period. The time integrated signal is compared with the predefined threshold signal. By comparing we get to know the presence of the primary user in spectrum. If the energy of the signal is greater than the predefined threshold, then H (b) is present in the spectrum. If the signal energy is less than predefined threshold, then H (b) is present in the spectrum.

$$H(a): Q < Y$$

$$H(b): Q > Y$$

Where Q - is energy signal Y - is threshold. The receiver signal is a specific part of the spectrum. While testing the hypothesis H (a) and H (b) we may get two type of errors one is detection probability (Dp) and another is False alarm probability (Fp). Detection probability means it detects a signal on a known frequency or considered frequency when it is truly present. Sometimes the Dp shows as absent but it was present. So, probability of detection should be more or large. And false alarm (Fp) mean false declaring of presence of the primary user. The value of false alarm should be small as possible.

Let b(P) is input signal at primary user, n(P) is noise signal it is obtained by using updating weight updates in feedback loop, z(P) is output obtained by using adaptive algorithm, M is the length in LMS.

performance is affected mostly by this noise change levels.

Depending on step size parameter 'S' of weight update equations, next weight can be estimated as w(P), then the expression for LMS weight update equation can be written as

$$w(P+1) = w(P) + S\, b(P)\, n(P) \qquad (1)$$

Computational complexity of adaptive filter algorithm is reduced by using signum function and it is expressed as

$$C\{b(P)\} = \begin{cases} 1: b(P) > 0 \\ 0: b(P) = 0 \\ -1: b(p) < 0 \end{cases} \qquad (2)$$

By using the above variant in input signal, computational complexity is reduced. LMS is having greater computational complexity so considered the clipped version of LMS (C LMS), then the input b(P) is taken as C[b(P)] as it changing the input vectors, then its weight update equation can be written as

$$w(P+1) = w(P) + S\, C\{b(P)\}\, n(P) \qquad (3)$$

Then to obtain weight relation of ECLMS method, the noise signal n(P) is changing by using signed function and it is expressed as

$$w(P+1) = w(P) + S\, b(P)\, C\{n(P)\} \qquad (4)$$

Weight relation for Data Error with Clipped LMS is obtained by substituting b(P) and n(P) with signed forms as

$$w(P+1) = w(P) + S\, C\{b(P)\}\, C\{n(P)\} \qquad (5)$$

Basic adaptive LMS technique is simple and for better convergence we are choosing the parameter size, then the weight updated time to time for every iteration. Tap coefficients also adapted based on the input filter conditions. For large input sensing, it has some noise limitation, so proposed error normalized least mean logarithmic square algorithm. It is considered as unique application algorithm of LMS. By considering this, signal levels at the output is varied according to the logarithmic cost functions which leads to faster convergence. Hence it overcomes the limitations of LMS algorithm and convergence is increased by using sign regressor functions. Mathematical modelling of Error Normalized Least Mean Logarithmic Square algorithm (EN LMLS) is

Let us consider, filter length is 'M', S is step size parameter
Tap Input is b(P) and filter length M is initialized then w(0) is considered as initial condition.
Then the input data b(P) is tapped by length M by 1 then it is expressed at time P as

$$P = [b(P), b(P-1) \; \dots\dots \; b(P-M+1)]^T,$$

From $\beta(P)$ in (6), then the resultant expression is

obtained as

$$w(P+1) = w(P) + \frac{1}{2\, n^T(p)\, n(p)} n(p) b(p) \quad (8)$$

Then the mean square error convergence bound of LMS is given as

$$0 < \beta' < \frac{2}{\boldsymbol{b}^T(p)\boldsymbol{b}(p)} \quad (9)$$

$\beta(P)$ in case of ENLMLS algorithmbecomes

$$\beta(P) = \frac{\beta'}{n^T(p)\, \boldsymbol{n}(p)} = \frac{\beta'}{||\boldsymbol{n}(p)||^2} \quad (10)$$

Small constant value ε is added for preventing denominator value is low

$$\beta(P) = \frac{\beta'}{\varepsilon + ||\boldsymbol{n}(p)||^2} (11)$$

b(P) is adaptive filter tap weight vector, d(P) is desired response at time P, n(P) is noise signal
w(P+1) is estimated tap weight vector to be computed at time P+1
Output of FIR filter is given as

$$z(P) = b^T(P)\, w(P) = w^T(P)\, b(P)$$

Cost function of conventional error signal n(P) is

$$F[n(P)] = E\left[\left(n(P)\right)^2\right] = E[|n(P)|]$$

Then the LMS recursion expression is written a

$$w(P+1) = w(P) + 2\,\beta(P)\, b(P)\, n(P) \quad (6)$$

where $\beta(P)$ is step size parameter varying with time it is selected so that a posterior error n*(P)

$$n^*(P) = (1 - 2\,\beta(P)\, b^T(P)\, b(P)\, n(P)) \quad (7)$$

The above equation is minimized in magnitude,

LMS weight update equation with $\beta(P)$ is obtained by replacing with 'S', then the weight update equation for ENLMLS is written as

$$\boldsymbol{w}(p+1) = \boldsymbol{w}(p) + \frac{\beta'}{\varepsilon + ||\boldsymbol{n}(p)||^2} \boldsymbol{b}(p) \left[\frac{\alpha(n(p))^2}{1+\alpha(n(p))^2}\right] \quad (12)$$

Then weight update relation for maximum ENLMLS for $n_{Li} \neq 0$ and $\varepsilon \neq 0$ becomes

$$\boldsymbol{w}(p+1) = \boldsymbol{w}(p) + \frac{\beta'}{\varepsilon + \max(||\boldsymbol{n}(p)||)^2} \boldsymbol{b}(p) \left[\frac{\alpha(n(p))^2}{1+\alpha(n(p))^2}\right] \quad (13)$$

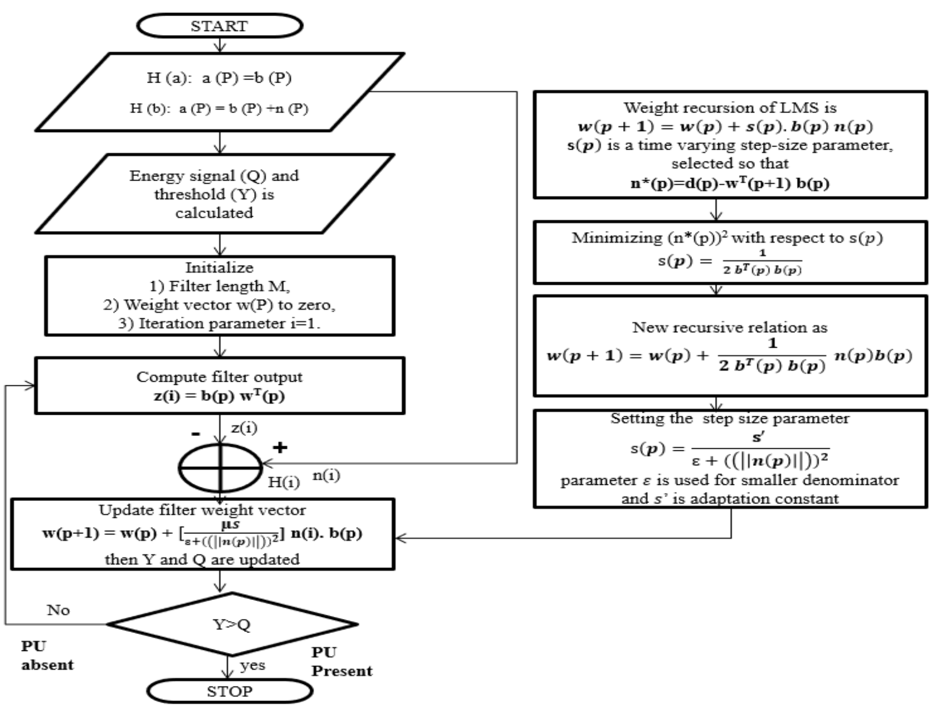

Figure 2: Flow chart of proposed ENLMLS for energy detection

For every iteration, weight update equation of LMLS equation is updated, then for better convergence and to reduce computational complexity of circuit sign regressor algorithm applied to weight update equation and its flowchart is shown in figure 2. Then by updating equation for every iteration primary user is identified using energy detection and to use this frequency in medical telemetry networks.

Sign function is added for decreasing computational complexity, then the sign version of ENLMLS are sign regressor algorithm, sign algorithm and sign sign algorithm then it is written as EN SRLMLS, EN SLMLS and EN SSLMLS

The weight relations for ENSRLMLS, ENSLMLS, and ENSSLMLS techniques becomes

$$w(p+1) = w(p) + \frac{S'}{\varepsilon + (||n(p)||)^2} C[b(p)]n(p)[\frac{\alpha(n(p))^2}{1+\alpha(n(p))^2}] \quad (14)$$

$$w(p+1) = w(p) + \frac{S'}{\varepsilon + (||\boldsymbol{n}(p)||)^2} b(p)C\left[n(p)\left[\frac{\alpha(n(p))^2}{1+\alpha(n(p))^2}\right]\right] \quad (15)$$

$$w(p+1) = w(p) + \frac{S'}{\varepsilon + (||\boldsymbol{b}(p)||)^2} C[b(p)]C\left[n(p)\left[\frac{\alpha(n(p))^2}{1+\alpha(n(p))^2}\right]\right] \quad (16)$$

Performance is improved by using sign regressor algorithm, using this sign regressor computational complexity is reduced. Hence, we preferred ENSRLMLS algorithm when compared to sign algorithm and sign sign algorithm.

III. RESULTS AND DISCUSSION

Performance of spectrum sensing using energy detection is analyzed using MATLAB. For the simulation analysis considered the noise variance as one, detection probability D_p, false alarm probability F_p is considered as 0.1, SNR range is taken between -25 dB to -15dB, for 10000 iterations N is simulated. Then from theoretical studied it is clear that for various values of N and for low SNR the error probability is decreased if the value of N is increasing. If the error probability is decreased as N value increases then the performance of cognitive radio systems for telemetry networks improved. Detection probability is also increased for low SNR values. For fixed threshold values also, detection probability is improved if its SNR value is low. Performance of energy detection deteriorates for very low SNR values. So proposed an adaptive algorithm for improving the energy detection performance. In this paper proposed an Error Normalized LMLS algorithm for improving detection performance by updating threshold value. Then the parameters detection probability D_p, false alarm probability $F_p$are studied for different SNR values. Then it is observed that by using adaptive filter algorithm detection probability performance is improved. It is also observed that performance of detection probability is improved for low SNR values as well as fixed threshold value. Adaptive filter error normalized LMLS improves the energy detector performance for SNR low values also. Probability detection performance is increased for the proposed error normalized least mean logarithmic square (EN LMLS) algorithm compared to spectrum sensing using energy detection alone. Identification of spectrum holes is also done faster in cognitive radio system, so that by using this frequency utilization we used this in wireless medical telemetry networks to give the treatment who are far away from the hospitals and elder patients. Energy detection performance is changes if there is an effect of noise uncertainties in the input signal. For improving detection probability in this noise uncertainty conditions adaptive filter algorithm is used. By using this adaptive filter algorithm noise is removed because for every iteration equation is updated using tap filet mechanism. It means if there is a noise in the equation then it is removed using adaptive filter and the output of filter is added with desired response equation, then we get the final updated equation. After that by using the theoretical threshold value and energy equations of hypothesis consideration, primary user absence or presence is identified. So that spectrum utilization is improved by using spectrum sensing. Even though there are some noise uncertainties are there in the resultant expression, it is due to the energy signal is correlated with some noise power values. It is removed by using signum function to weight update equations.

For primary user if we give more weights, then probability detection is increases and spectrum utilization is also used in better way. By using threshold point, it will decrease miss detections so that interference to primary user is reduced. From theoretical studies it is clear that, missed detection probability decreases if SNR value increases. Then the primary user is selected without any interference to secondary channel and its channel gain is depends on the SNR value. In earlier studies for energy detection we mainly study about parameters threshold value, false alarm probability and detection probability value is selected based on sensing. SNR is inversely proportional to Probability false alarm. For low SNR values, false alarm probability is high and vice versa By using proposed method, detection performance is improved by noise uncertainty is introduced to the input signal in order to make use of low snr signals. Improvement in probability detection is shown in terms of faster convergence. Signum function is applied as to weight updated equation of EN LMLS algorithm. Three variants are available for the signum function applied equation: they are sign regressor, sign algorithm and sign sign algorithm. By using every signum function it is updated with weight updated equation of EN LMLS algorithm and it is simulated. Then we observed that sign regressor based adaptive filter algorithm is converged faster compared to other two algorithms. It is explained also with computational complexity to better understanding

By using sign regressor function to adaptive algorithm convergence is improved because computational complexity is decreased. For estimating algorithm, the amount of multiplications required is determined, it is not only focus on accurate analysis for complexity reduction also it evaluates the adaptive EN LMLS algorithm. Generally, LMS needs M+1 multiplication also one addition is required for calculations, then the weight update equation is updated. While for computing sign regressor based EN SRLMLS requires 2M+1 multiplication only. For the case of other signed EN LMLS algorithm it required 2M+1 multiplication. Hence it is clear that for EN SRLMLS requires less multiplications only and computational complexity is also less compared to sign and sign sign based EN LMLS methods. Their computational complexity is shown in table 1.

Table I. Computations Required for LMS and its Sign Variants

S.No.	Algorithm	Multiplications	Additions
1	LMS	M+1	M+1
2	ENLMLS	2M+7	2M+2
3	ENSRLMLS	2M	2M+2
4	ENSLMLS	2M+5	2M+2
5	ENSSLMLS	M+2	M+2

Proposed ENLMLS provides less complexity for performing computations for desired spectrum sensing input frequency signal and for identifying spectrum holes in cognitive radio networks. Convergence curve for the proposed ENLMLS algorithm is shown in figure 2 and for their sign variants also. Then it is clear that proposed EN LMLS is converged faster when compared to LMS algorithm. Also, it shows that sign regressor based EN LMLS algorithm is converged better because its computations are less when compared to LMS and other two sign algorithms. Then it clear that EN SRLMLS converges faster when compared to EN SLMLS and ENSSLMLS.

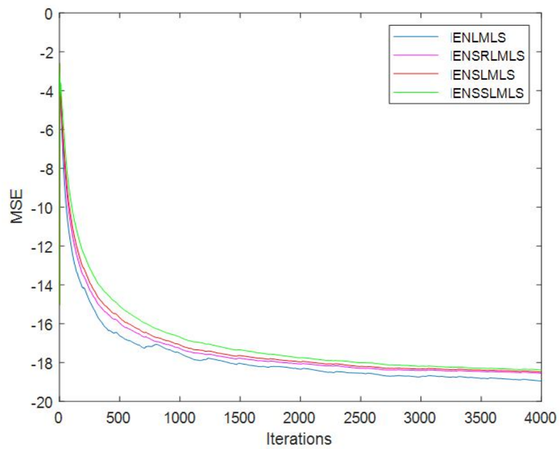

Figure 3: Convergence characteristics of ENLMS and its sign variants in energy detection process

IV. CONCLUSION

Cognitive radios systems are considered for medical telemetry networks. In the cognitive radio systems, telemetry network technology is used to collect the information from the various data sources using a set of automated communication processes, and transmitted to the receiving equipment for examining tasks. In wireless communication, medical telemetry is generally used to health protection applications like monitoring a patient's vital signs example: pulse and respiration using RF (Radio Frequency) communication. In the cognitive radio Spectrum sensing is one of the main techniques, it can be used in the medical telemetry field. The applications of MBAN include both wearable and implantable sensors for remote health care monitoring of patients. For health care monitoring in medical telemetry spectrum sensing uses energy detection technique. Then for convergence and to reduce noise levels in received signal proposed ENLMLS algorithm and it shown better results in terms of increased detection probability. Sign version of proposed EN LMLS gives better results when compared to ENLMLS algorithm.

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